Atmospheric Measurement Techniques Discussions

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Reply on CC3

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Author comment on "Four-dimensional mesospheric and lower thermospheric wind fields using Gaussian process regression on multistatic specular meteor radar observations" by Ryan Volz et al., Atmos. Meas. Tech. Discuss., https://doi.org/10.5194/amt-2021-40-AC4, 2021

Thanks for the comment!

1. (Comparison to classical 2DVAR data assimilation) Can you point to a reference to which we might compare? In general we expect similarities with many statistical estimation approaches, with the primary differences arising from the specific formalism used and how that allows one to express the prior knowledge and constraints on the estimate. We think the strengths of the GPR method are that specifying a covariance function allows one to easily apply physical intuition, that it works in 4 dimensions at once and does not impose a gridding of the measurements or estimates, and that it is natural to carry through and compute uncertainties on the estimates.

In particular concerning vertical averaging and accomodating strong vertical shears, the natural way to express that in the GPR framework is to enforce a small value for the covariance length scale in the vertical dimension. The examples in this paper use a fitted value for the vertical length scale of 3 km, which arises both from what the density of meteor measurements will support and also from the observed vertical correlations particular to the winds seen with these data. So we can say that the averaging is approximately over a vertical region of 3 km and that any sharper vertical shears will be smoothed over (i.e. the effective vertical resolution is 3 km). It is certainly possible to manually set the covariance parameters to better investigate vertical shears in particular if that is what the user sets out to do. The GPR framework provides great flexibility, and we certainly don't think that we have already arrived at a form for the covariance functions that achieves best case performance in general and especially for specific analysis objectives.

2. (WGS84 geometry) There are two relevant applications of applying WGS84 geometry related to this work: in geolocating the meteors and calculating the corresponding Bragg vector in the meteor local ENU coordinate system, and in estimating the winds from the meteor data. This paper only lightly touches on the first case in assuming that the meteor radar data has already been processed into meteor observations complete with a Doppler shift, geodetic latitude and longitude, and Bragg vector. The procedure to get to that point is exactly the same as in the works cited in Section 4, e.g. Chau and Clahsen (2019), although full detail can be found in Clahsen (2018) [full citation below], with the meteor geolocation procedure also described in Stober et al. (2018). We will clarify this in the next revision.

For the second case in applying WGS84 geometry within the wind estimation, we describe our procedure of using a local azimuthal equidistant projection in Section 2. This application is new to this work, although the azimuthal equidistant projection using the WGS84 sphereoid is well-known. We use a projection only for computational efficiency, as it is much easier and faster to work in a Euclidean coordinate system when performing the estimation than to use the full geodetic computations, although it is possible to do the latter.

3. (Vertical winds) We agree on the challenges of estimating vertical winds and the care that must be taken in doing so. This procedure takes into account the projection effects that result in the vertical wind component usually not being as well-characterized as the horizontal components, and this relative uncertainty is quantified in the posterior estimated variances. This is best demonstrated in the simulation results and in particular Figure 4. In general, the user of this technique can impose their prior belief in generally small vertical wind values by appropriately setting a small value for the vertical wind covariance amplitude or by checking that fitted values correspond to that expectation.

There are a few locations in the examples where the estimated vertical wind exceeds a magnitude of 10 m/s. We don't make a note of it because the estimated confidence interval of the vertical wind at those points (and indeed, all over) is large enough to allow for a true value that is in line with what has been observed in the MLT region by different instruments and groups, e.g. Vierinen et al. (2013), Lu et al. (2017), Chau et al. (2020). These examples show MLT vertical winds on the scale of a few meters per second at minute to hour timescales.

Additional References

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